ECG Data Compression Using Adaptive Wavelet Packets

by

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CERTIFICATE

This is to certify that the work contained in the thesis entitled ECG Data Compression Using Adaptive Wavelet Packets by Suyog Moogi has been carried out under my supervision and that this work has not been submitted else where for a degree

Dr G C RAY
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Abstract

The electrocardiogram (ECG) is a quasiperiodic signal and is extremely well suited for Long Term Prediction (LTP) The signal is first segmented into beats and every sample within a beat is predicted from samples around the corresponding point in the previous beat The residual signal after prediction has a much lower dynamic range and can be encoded with fewer bits per sample This gives a first stage of compression The residual signal is then subjected to an Adaptive Wavelet Packet (AWP) decomposition using a pair of quadrature mirror filters The coefficients within each packet are then selectively discarded using an energy threshold criterion and the zeros are runlength coded This gives a second stage of compression The combination of the two methods gives very high compression ratios with very small reconstruction error It also retains any abnormalities present in isolated beats

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Chapter 1

Introduction

1 1 Biological Preliminaries

The electrocardiogram (ECG) is one of the simplest and most valuable tool for detection of a wide variety of heart diseases As a result a lot of ECG data is generated, which warrants the need for effective compression techniques for archiving purposes

A normal ECG signal beat would be as shown in figure 1 1 The various regions

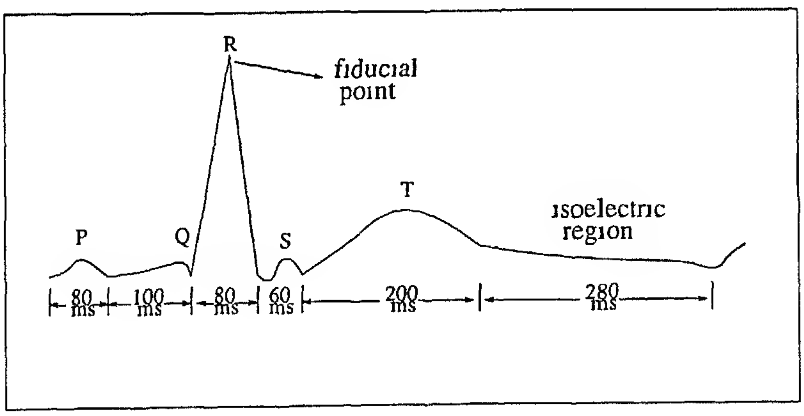

Figure 1 1 ECG signal beat

and their typical durations are also indicated The heart consists of two upper chambers called the auricles and two lower chambers called the ventricles The different regions in the wave are characterised by

- P Atrial depolarisation
- Q Conduction through atrio ventricular (AV) node
- R Ventricular Repolarisation
- S+T Ventricular depolarisation

Both the auricles contract simultaneously and pump the blood to the ventricles Both the ventricles also contract simultaneously 75 percent of the total work is done by the left ventricle which pumps blood all over the body 20 percent of the total work is done by the right ventricle as it pumps blood to the capillaries of the lungs As a result a lot of synchronization is required in the operation of the various muscles and the wave shape of the ECG signal gives an indication of the normal functioning of the heart

1 2 Review of Techniques Used For ECG Compression

The ECG data compression techniques may be broadly classified into three categories

1. Direct data methods
2. Transformation methods
3. Parameter extraction methods

1 2 1 Direct Data Methods

They act on the ECG signal directly and try to remove the redundancies present in it The common techniques which fall under this category are briefly reviewed

1. Turning Point (TP) algorithm The TP algorithm has the greatest ease of implementation and gives a fixed compression ratio of 2 1 It analyzes the

trends of the sampled points and stores only one out of a pair of consecutive points It also retains all the peak and valley points at which the slope of the signal changes

2 Amplitude zone time epoch coding (AZTEC) The AZTEC replaces a sequence of sample points with plateaus and slopes Only two parameters are trans mitted either the amplitude and length of a plateau or the final elevation and duration of a slope Although the AZTEC gives a compression ratio of about 5 1, the reconstructed signal has a step like quantization effect which is unfamiliar to medical personnel Therfore an additional curve smoothing algorithm has to be used Although the smoothing reduces the distortion information of the amplitudes of QRS peaks and valleys are lost which are important in the diagnosis of certain diseases

3 Co ordinate reduction time encoding system (CORTES) The CORTES is a hybrid of TP and AZTEC algorithms that is designed to take advantage of the strengths of each method It simultaneously applies AZTEC to the isoelectric region and TP to the clinically significant higher frequency region like the QRS complex Once an AZTEC plateau is produced CORTES saves the AZTEC data if the plateau is longer than a particular threshold or else it stores the TP data Only AZTEC plateaus are generated no slopes are produced The CORTES gives a compression ratio which is slightly less than that given by AZTEC but the quality of the reconstructed signal is much better

4 The Fan algorithm This algorithm is illustrated in the following figure The first data point at time instant T0 is accepted as a permanent data point Two slopes (U1 L1) are drawn between the originating point and the next sample plus a specified threshold ($\pm\epsilon$) If the third point falls within the area bounded by U1 and L1 then new slopes U2 and L2 are drawn and the most converging slope (U1 and L2 in the figure) are retained The process is continued till a sample falls outside the area bounded by the most converging slopes The sample immediately preceeding it is saved as the next permanent sample This permanent point becomes the new originating point of the algorithm

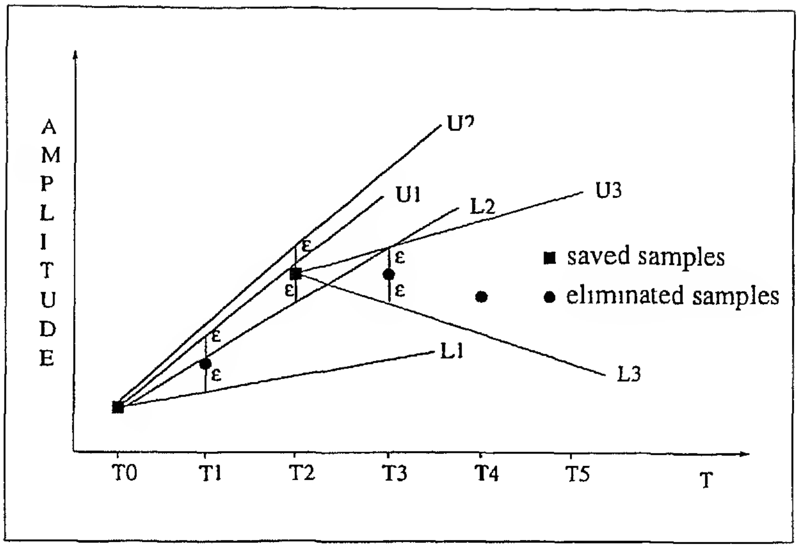

Figure 1 2 The FAN algorithm

1 2 2 Transformation Compression Methods

The main idea behind the transform technique is that the data in the time domain is transformed to some other domain like the frequency domain in which a major portion of the signal energy is packed into very few coefficients As a result only those few coefficients are retained and the others are discarded i e set to zero The zeros can then be run length coded to give a compression For signal reconstruction an inverse transform is performed and the original signal is recovered with a certain degree of error

Many discrete orthogonal transforms have been employed such as the Karhunen-Loeve Transform (KLT) Fourier Transform (FT) Cosine Transform (CT), Walsh Transform (WT) Haar Transform (HT) etc The optimal transform is the KLT where the basis vectors are the eigen vectors of the correlation matrix of the input sequence It is optimal in the sense that least number of orthonormal functions are needed to represent the input signal for a given RMS error The KLT results in decorrelated transform coefficients and minimizes the total entropy as compared to any other transform The disadvantage is the computation time required to calculate the KLT basis functions and hence some sub optimum transform with a fast algorithm like FT WT, CT have been used The basis vectors of these

transforms are known before hand and are input independent Their performance is upper bound by the KLT

1 2 3 Parameter Extraction Methods

A preprocessor is employed to extract some features that are later used to reconstruct the signal Methods that belong to this group are Linear Prediction Peak Picking Syntactic methods and Neural Nets method In linear prediction the signal is first segmented into blocks and a set of prediction coefficients is determined for each block Using these coefficients every sample within the block may be predicted as a linear combination of the past few samples So for the entire beat one has to store only the prediction coefficients and the residual error As the residual signal has a much lower dynamic range than the original it can be encoded with fewer bits to give a compression If the tolerance on the reconstruction error is not rigid the residual may not be encoded at all

1 3 Organisation of The Thesis

In this thesis the effects of combining two methods of compression is investigated The first method is Long Term Prediction (LTP) which belongs to the class of parameter extraction methods The residual after LTP is subjected to Adaptive Wavelet Packet (AWP) decomposition, which belongs to the class of transformation methods In chapters two and three the LTP and AWP decomposition methods are discussed respectively Chapter four describes how the two methods have been combined and gives the implementational details Chapter five discusses the results and compares it with LTP and AWP applied individually It also discusses the effects of 50 Hz line interference on the compression ratio and reconstruction error The ability of the algorithm to retain abnormalities in isolated beats is also shown

Chapter 2

Long Term Prediction

2 1 Introduction

ECG compression using Long Term Prediction (LTP) was suggested by Gil Nave and Arnon Cohen in [1] It is a parameter extraction method based on Linear Predictive Coding (LPC) In the conventional LPC method the nth sample of a signal is predicted from its past p samples The error between the predicted and actual samples is sent or stored instead of the sample itself Since the variance of the error is less than the original signal it requires fewer bits for encoding It has been shown [4] that correlation between adjacent samples of ECG is very low and very little is gained by taking $p > 2$ In LTP advantage is taken of the fact that ECG is quasi periodic i e a similarity exists between adjacent beats This is clearly indicated by the autocorrelation of the ECG data plotted in figure 2 1

The prediction of the nth sample is made using the samples around the corre sponding point in the previous beat This is indicated in figure 2 2 This kind of long term correlation has also been used in speech analysis for pitch detection

2 2 Long Term SAR Models

The autoregressive model (AR(p)) has been applied since a long time for the mod elling and analysis of signals For the signals which exhibit some sort of periodicity

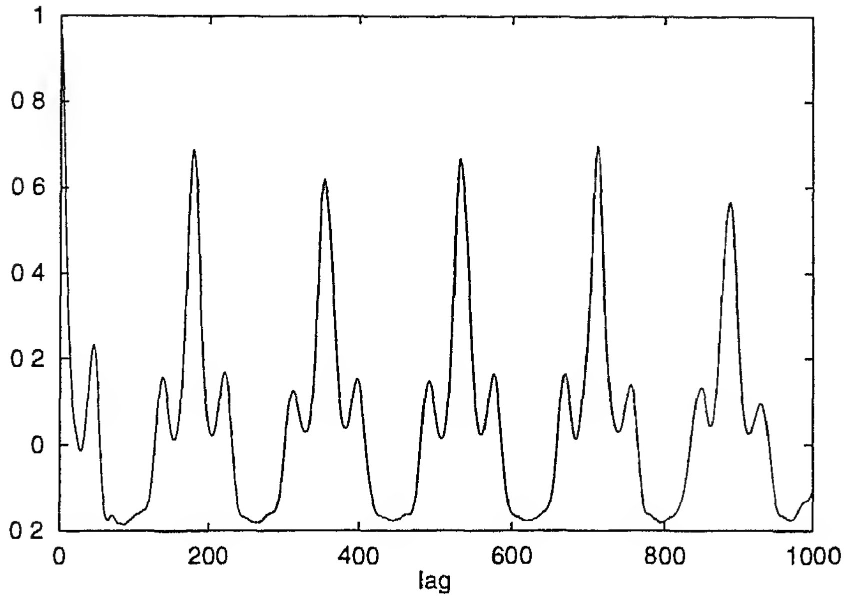

Figure 2 1 Autocorrelation function of an ECG record

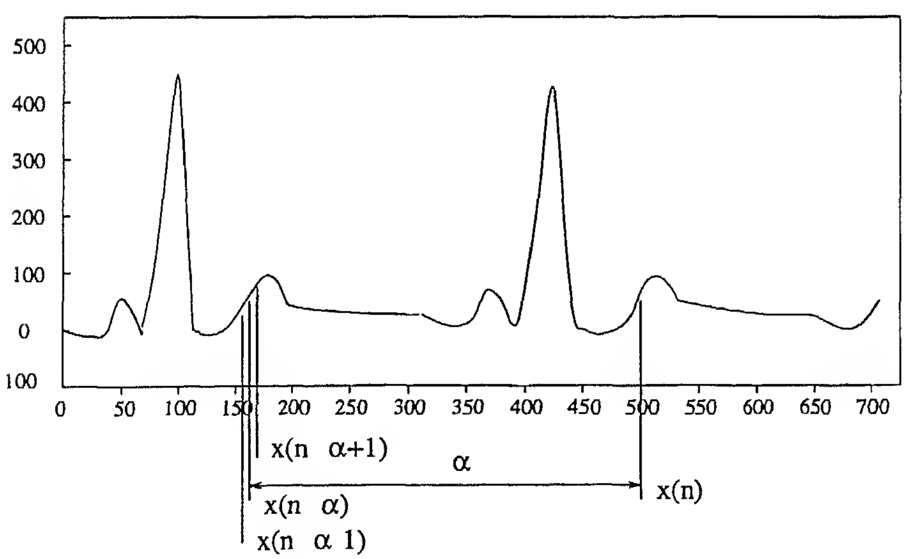

Figure 2 2 SAR model for ECG

the Subset Autoregressive (SAR) time series model is more suitable The SAR $(\alpha\ m)$ $\alpha^T = (\alpha_1\ \alpha_2\ \alpha_3\ \quad \alpha_m)$ model for a time series is defined as

$$y(n) = \sum_{i=1}^{m} a_\alpha\, y(n - \alpha_i) + u(n) \tag{2 1}$$

where $y(n)$ is the nth sample α_i and a_α are the ith prediction lag and ith prediction coefficient respectively and u(n) is the nth sample of a zero mean stationary white innovation The SAR $(\alpha\ m)$ model is an AR model of order α_m with all coefficients a_j, $j \notin \alpha$ set to zero The speech signal during voiced utterances exhibits some periodicity and hence advanced speech compression systems based on CELP use SAR models However in speech literature the terminology LTP is used instead of SAR The main problems associated with SAR $(\alpha\ m)$ modelling are the estimation of the model order α_m the subset α selection and the estimation of the prediction coefficients a_j

In applying the SAR $(\alpha\ m)$ model to the ECG, equation (2 1) is slightly modified The nth sample is given by

$$y(n) = \sum_{j=1}^{q} a_{0\,j}\, y(n - j) + \sum_{i=1}^{m} \sum_{j=-p}^{p} a_{i\,j}\, y(n - \alpha_i + j) + u(n) \tag{2 2}$$

Thus the nth sample of the sequence is given as a linear combination of q adjacent past samples (AR(q)) and m groups of samples centered around the $(n - \alpha_i)$th sample $i = 1\ 2\ 3, \quad m$ This modified model is denoted as SAR $(q\ \alpha, p\ m)$ where p is the m dimensional vector $p^T = [p_1\ p_2\ \quad , p_m]$ The correlation with the few adjacent past samples is considered by the conventional short term linear prediction of order q and the correlation with the previous beats is considered by the LTP

2 3 Simplified SAR Model

For the application to the ECG, the model is further simplified to SAR $(0\ \alpha\ p\ 1)$ where only one adjacent beat is used and no use is made of the AR(q) part Since the innovation sequence $u(n)$ is inaccessible the nth sample is predicted by

$$y(n) = \sum_{i=-p}^{p} a\, y(n - \alpha + i) \tag{2 3}$$

and the resıdual sıgnal $r(n)$ ıs defined as

$$\begin{aligned} r(n) &= y(n) - y(n) \\ &= y(n) - \sum_{=-p}^{p} a_\imath y(n - \alpha + \imath) \end{aligned} \tag{2 4}$$

The predıctıon coefficıents $\{a_\imath\}_{\imath=-p}^{p}$ are determıned so as to mınımıze the total squared error over a wındow of N samples

$$E = \sum_{n=1}^{N} r^2(n) \tag{2 5}$$

The mınımızatıon process leads to the followıng lınear set of $2p+1$ eqatıons

$$\begin{aligned} \sum_{=-p}^{p} a_\imath \varphi(\alpha - \imath \;\; \alpha - \jmath) &= \varphi(0 \;\; \alpha - \jmath) \\ \jmath &= -p, -p+1 \qquad p \end{aligned} \tag{2 6}$$

where

$$\varphi(\imath \;\; \jmath) = \sum_{n=1}^{N} y(n-\imath) y(n-\jmath) \tag{2 7}$$

Equatıon (2 6) may be wrıtten as

$$\Phi a = \varphi \tag{2 8}$$

where

$$\begin{aligned} a^T &= [a_{-p} \;\; a_{-p+1} \qquad a_p] \\ \varphi^T &= [\varphi(0 \;\; \alpha+p) \qquad \varphi(0 \;\; \alpha-p)] \end{aligned}$$

and

$$\Phi = \begin{bmatrix} \varphi(\alpha+p, \alpha+p) & & \varphi(\alpha+p \;\; \alpha-p) \\ & & \\ \varphi(\alpha-p, \alpha+p) & & \varphi(\alpha-p \;\; \alpha-p) \end{bmatrix}$$

The matrıx Φ ıs a symmetrıc posıtıve semı defınıte matrıx and ıts ınverse may be efficıently calculated by Cholesky decomposıtıon method The SAR coefficıents

may be calculated by the solution of equation (2 8) and the original signal may be obtained by the synthesis equation (2 4)

$$\begin{aligned} Y(z) &= \sum_{=-p}^{p} a_i Y(z) Z^{-\alpha+i} + R(z) \\ &= Y(z)P(z) + R(z) \end{aligned} \tag{2 9}$$

where $P(z) = \sum_{i=-p}^{p} a_i Z^{-\alpha+i}$ is a SAR polynom The compression and reconstruction schemes are shown in figure 2 3

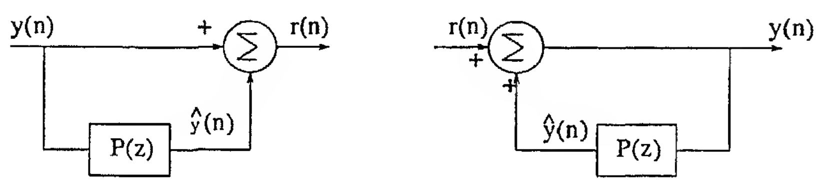

Figure 2 3 Compression and reconstruction schemes

2 4 Residual Signal Encoding

The coefficient b is determined by minimizing the mean squared error between $r(n)$ and its estimate $r(n)$ over a set of M samples and is given by

$$r(n) = br(n-1) \tag{2 10}$$

Thus the residual error signal is given by

$$e(n) = r(n) - br(n-1) \tag{2 11}$$

The coefficient b is determined by minimizing the mean squared error between $r(n)$ and its estimate $r(n)$ over a set of M samples and is given by

$$b = \frac{\sum_{n=1}^{M} r(n)r(n-1)}{\sum_{n=1}^{M} r^2(n)} \tag{2 12}$$

2 5 Adaptive Quantization and Entropy Coding

Uniform quantizers with N levels and quantization step q have a dynamic range of Nq in which the quantization error is bound by $| q/2 |$ For stationary processes uniform quantizers are designed to meet the conditions

$$x_{max} = m_x + \gamma\sigma_x \quad x_{min} = m_x - \gamma\sigma_x \tag{2 13}$$

where m_x and σ_x are the expected value and standard deviation of the quantizers input respectively, and γ is a loading factor The error signal to be quantized here is a non stationary process Infact it is quasi stationary i e, stationary within a beat Therefore a time varying quantizer is needed where the values of m_x and σ_x are estimated for each beat In each beat the quantizer has a different dynamic range and a particular symbol may represent a different quantization level The symbols used may not be uniformly distributed and this source redundancy may be removed by using Huffman entropy coding Here symbols with higher probability are allocated lesser bits and symbols with lower probability are allocated more bits This gives a net reduction in bit rate

2 6 Results

The proposed system was tested by the authors using an in house database consisting of ECG records of forty patients representing various pathologies The signal was sampled at 250 Hz and quantized to 10 bits per sample Thus the input bit rate was 2500 bits/second Using the LTP method, the compressed bit rate was in the range of 71 490 bits/second The lower bit rate corresponds to zero quantization levels i e the residual was not encoded at all and the higher bit rate corresponds to six quantization levels The LTP method was shown to be much superior to conventional STP in terms of the bit rates and reconstruction error

Chapter 3

Adaptive Wavelet Packet Decomposition

3 1 Introduction

The principle behind wavelet packets can be illustrated by an analogy to musical notes To store music in terms of a sequence of sound wave amplitudes will require atleast 8000 samples per second to maintain a reasonable fidelity Therefore half a million pieces of information would be required to store one minute of music The same minute of music could be transcribed by a couple of hundred musical notes on a score By combining several characteristic features of sound, such as pitch duration and intensity into a single object musical notes provide a tremendously economical way to represent musical information Wavelet packets are essentially mathematical musical notes Each wavelet packet represents a specific mathematical pattern or template parametrized by scale frequency and position which can be used to efficiently express general kinds of information

Just as there are many different instruments which may be used to produce musical notes, there exist many different libraries of wavelet packets Associated with each library of wavelet packet is a pair of quadrature mirror filters (QMF s) One is defined as a low pass filter and the other as a high pass filter The QMF s define two orthonormal projection operators $F0$ and $F1$ which may be applied to a

vector For each vector V $F0(V)$ and $F1(V)$ are vectors which contain half as many entries as V and $F0(V) \perp F1(V)$ Hence application of both operators generates a set of decorrelated transform coefficients

The wavelet packet transform of a finite sampled data is computed by successively applying the QMF projections as illustrated in figure 3 1 to generate a binary tree of transform coefficients Associated with each coefficient are three location

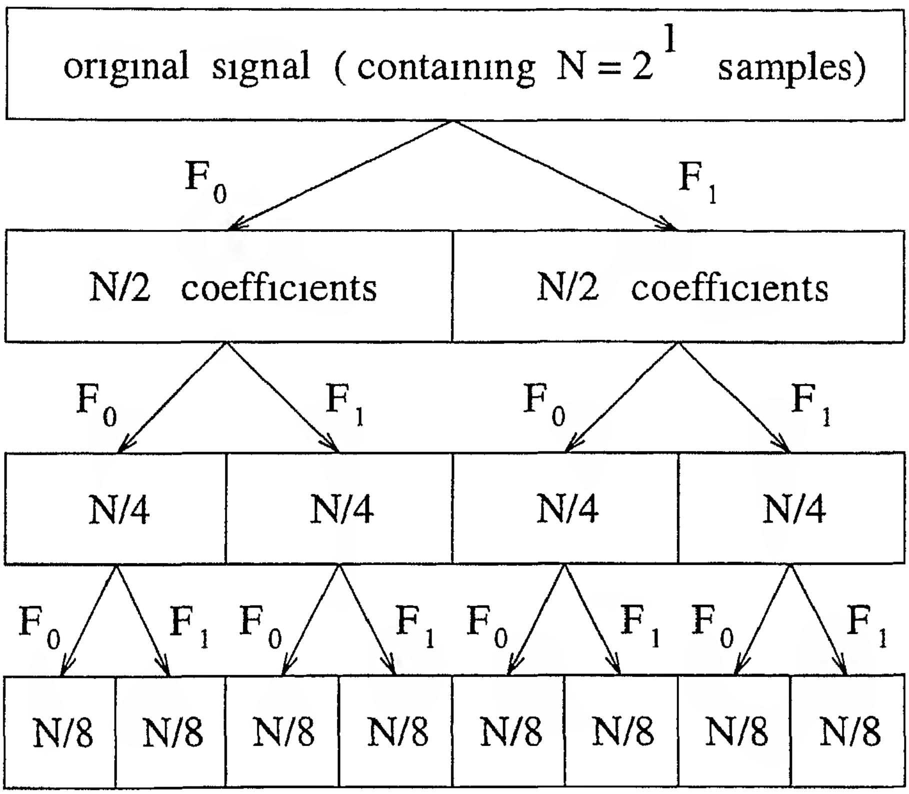

Figure 3 1 Wavelet packet tree

parameters— level within the tree vertex along a level and entry within a vertex— which determine the scale, frequency and position respectively of the underlying wavelet packet pattern Any collection of vertices which satisfies the property that each path from the root to a leaf contains exactly one vertex from the collection, constitutes an orthonormal expansion of the original signal

3 2 Algorithm for ECG Data Compression

An algorithm for ECG data compression was suggested in [2] For compression the criterion for adaptive decomposition is to minimize the information content of the signal The measure of information may be based on entropy or on the energy content of the transformed signal As shown in figure 3 2 the input vector is first split using a pair of QMF's and then downsampled by a factor of two At every stage

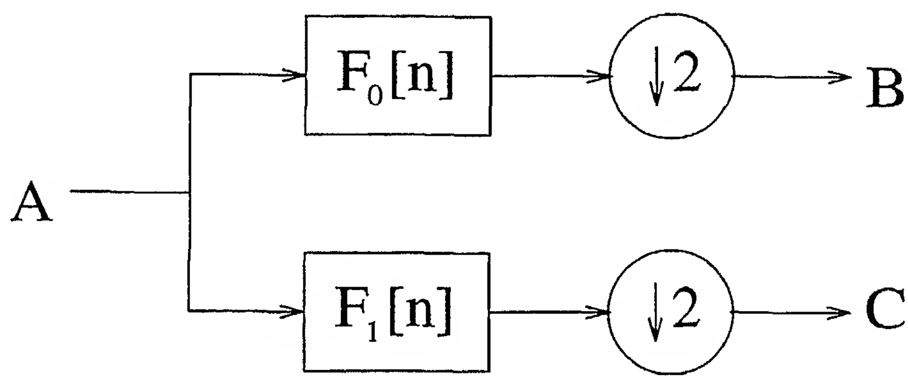

Figure 3 2 Wavelet packet decomposition using QMF s

of decomposition a measure of energy is obtained and a decision is made whether to split or terminate the branch Once an optimal basis is obtained the coefficients within each packet are discarded using a thresholding criterion This thresholding may be done in any of the following ways

1 absolute cut off—for any $\epsilon > 0$ set a coefficient $c = 0$ if $| c | < \epsilon$

2 using a local measure of energy $| x |^2$ discard any coefficient for which $| c | < \epsilon | x |^2, 0 < \epsilon \leq 1$

3 coefficients may be discarded on an entropy criterion

The algorithm may thus be summarized as

A] At A Find the measure of information (M) of the signal $x[n]$

If $M > T$ (threshold) THEN

pass the signal through a set of QMF s $F0$ (low pass) and $F1$ (high pass) followed by decimation, i e split

ELSE

threshold the coefficients

ENDIF

B] Repeat the above procedure recursively at B C and at other stages of decomposition

The resulting non zero coefficients are then quantized to suitable number of levels and the zeros are runlength coded to give compression

3 3 Results

The authors tested the algorithm on an ECG signal sampled at 1000 Hz with a resolution of 12 bits/sample Daubechies 20 point filter was used for the QMF s The non zero coefficients were scaled to 8 bits/sample A threshold for discarding the coefficients of three times the normalized local energy was found experimentally to be optimum The authors have claimed a compression ratio of 10 62 with a reconstruction error expressed in PRD of 5 92 The PRD is defined in equation (4 1) The adaptive wavelet packet (AWP) decomposition has been shown to provide better compression ratio for ECG signals than wavelet packet decomposition since it avoids the rigid nature of decomposition which is totally independent of the spectral content of the signal and provides a better error control by selectively discarding the coefficients

Chapter 4

Implementational Details

4 1 Data Acquisition

The LTP and AWP methods as suggested by their authors have been described in chapters two and three respectively This Thesis investigates the effects of combining these two methods This chapter gives the implementational details of the compression decompression schemes The algorithm has been tested on the ECG data picked up in Dr G C Ray's laboratory The signal has been amplified and sampled at an interval of 5 ms and quantized to 12 bits A quantized value of +2047 corresponds to +5V and 2047 corressponds to 5V The signal has also been filtered using a 50 Hz notch filter to remove the line interference Although the noise has been attenuated to a great extent it has not been removed completely The effects of this noise on the compression ratio and reconstruction error has been dealt with in the next chapter

4 2 Compression Scheme

The algorithm has been designed to compress blocks of 4096 samples which corresponds to about 20 seconds of data The first step is to segment the data into individual beats for which the fiducial point has to be determined The fiducial point is the peak point in the QRS complex as indicated in figure 1 1

4 2 1 Determination of RR Interval

To determine the fiducial point the point of maximum amplitude within a beat has to be determined The data is partitioned using an amplitude threshold considering only those points which are above the threshold For these points the index of the point having the maximum amplitude is located Once a maxima is obtained a certain interval of time is skipped to search for the maxima in the next beat In this way all the fiducial points are located The beginning of each beat is then arbitrarily set to 150 ms prior to the fiducial point The beat then extends from the beginning of this beat to the beginning of the next beat For the given data this ensures that the P wave and the T wave are also included within the same beat as the QRS complex although this is not essential for the algorithm

4 2 2 Residual Signal

Once the data block is segmented into individual beats the first beat is stored as it is From the second beat onwards the SAR (0 α 2 1) model of LTP is used The samples from the second beat are predicted from the samples around the corresponding point in the first beat and so on The prediction lag α in (2 3) is taken as the R R interval between the present beat and the previous beat To find the prediction coefficients (2 8) has to be solved where φ and Φ are determined using (2 7) To solve (2 8) the Cholesky decomposition method ([5] chap 8) may be used effectively since matrix Φ is symmetrical Once the prediction coefficients are obtained (2 4) is applied to get the residual signal The first beat of the input and the residual after LTP is shown in figure 4 1 The residual has a dynamic range which is roughly one eighth of the input It may thus be coded with three lesser bits per sample which does not give sufficient compression The dynamic range as obtained here is much higher than that obtained in [1] primarily due to line interference This aspect is dealt with in greater detail in the next chapter

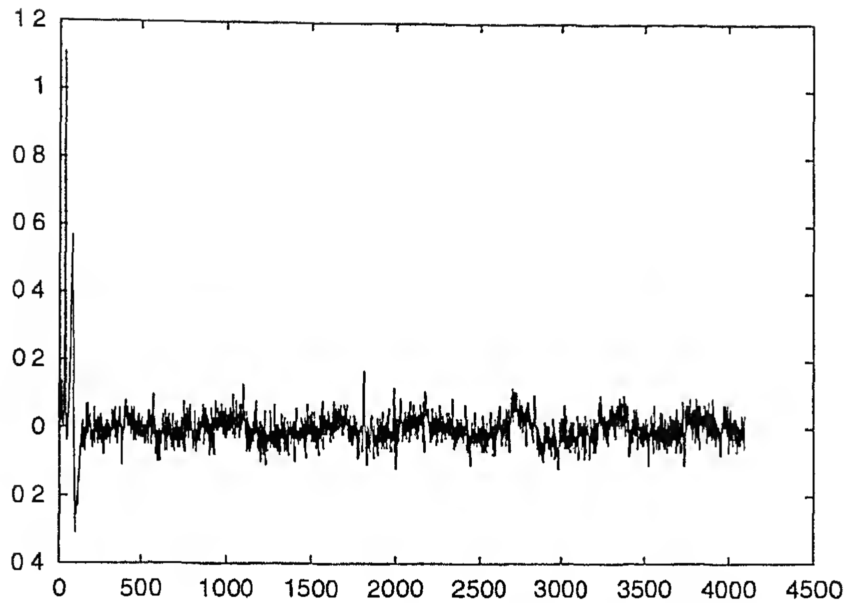

Figure 4 1 Residual signal after LTP

4 2 3 AWP Decomposition

The residual signal is then subjected to an AWP decomposition as described in chapter 3 The decomposition of the residual which is essentially the unpredictable part of the signal or noise needs a little clarification This is considered at the end of the chapter For the QMF's Daubechies 12 point filter is used whose coefficients are given in table 4 1

$F0[0]$	0 016387	$\Gamma0[6]$	0 076489
$F0[1]$	0 041465	$F0[7]$	0 059434
$F0[2]$	0 067373	$F0[8]$	0 023680
$F0[3]$	0 386110	$F0[9]$	0 005611
$F0[4]$	0 812724	$F0[10]$	0 001823
$F0[5]$	0 417005	$F0[11]$	0 000721

Table 4 1 Daubechies 12 filter coefficients

The relationship between the lowpass and highpass filters and their corresponding synthesis filters are as follows

$$\left.\begin{aligned} F1[i] &= (-1)^i \times F0[11-i] \\ G1[i] &= F1[11-i] \\ G2[i] &= (-1)^{11-i} \times F1[i] \end{aligned}\right\} 0 \le i \le 11$$

A dual thresholding criteria is used to determine the extent of decomposition The decomposition of a particular packet is terminated either if its energy content is less than ten percent of the input energy or if the packet size is less than thirty-two Once the decomposition is complete an energy thresholding criterion is applied to set the coefficients within each packet to zero if its contribution to the packet energy is less than one percent All these three parameters are variable and may be adjusted to get a suitable trade off between compression ratio and reconstruction error If a coefficient satisfies the thresholding criterion, it is set to zero only if there are three or more consecutive zeros, otherwise the coefficient is retained The non zero coefficients are then quantized to 8 bits and the zeros are runlength coded The residual signal after decomposition and thresholding is shown in figure 4 2 and after quantization and runlength coding is shown in figure 4 3

4 2 4 The Compressed Block

The quantized data along with the overheads constitute the compressed block The transformed data is encoded into eight bits The various overheads along with their bit allocation is shown in table 4 2

The input data has been quantized to 12 bits The compression ratio is defined as the input bit rate divided by the output bit rate While calculating the compression ratio, the first beat is not considered since it is retained as it is

4 3 Decompression Scheme

The decompression scheme is quite simple The overhead data like the number of beats, their starting indices the number of packets and their starting indices and

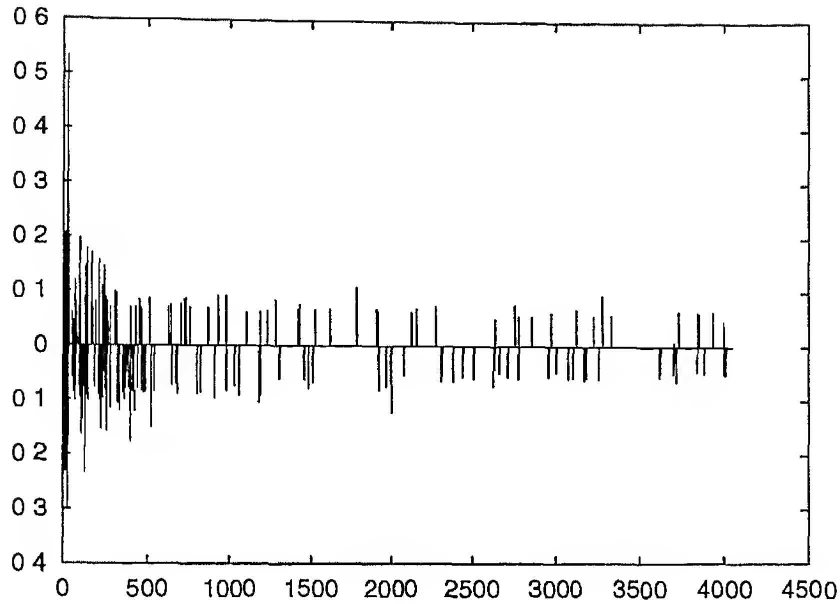

Figure 4 2 Residual signal after transformation and thresholding

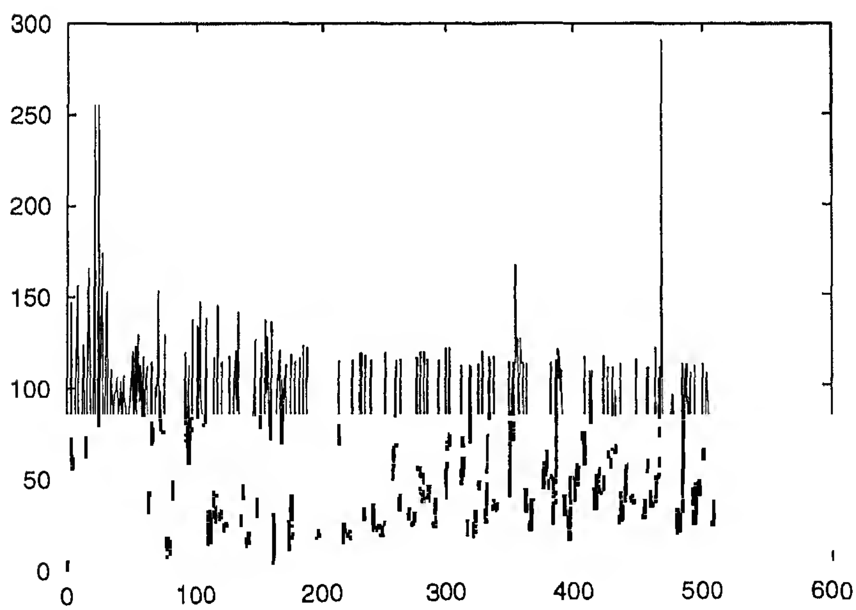

Figure 4 3 Transformed signal after quantization and runlength coding

number of beats	6 bits
length of input signal	12 bits
number of packets	6 bits
transform length	12 bits
starting index of each beat	12 bits
starting index of each packet	12 bits
prediction coefficients	6 bits

Table 4 2 Bit allocation for overhead data

the prediction coefficients are sequentially read from the compressed block Then the quantized coefficients are read Adequate zeros are added in proper places to decode the run length code The decomposition is then reversed starting with the smallest packets using the synthesis filters and the residual signal is recovered The residual signal after synthesis is shown in figure 4 4 Using the residual signal and the prediction coefficients the original signal is reconstructed Figure 4 5 shows the original and the reconstructed signals The reconstruction error is defined by

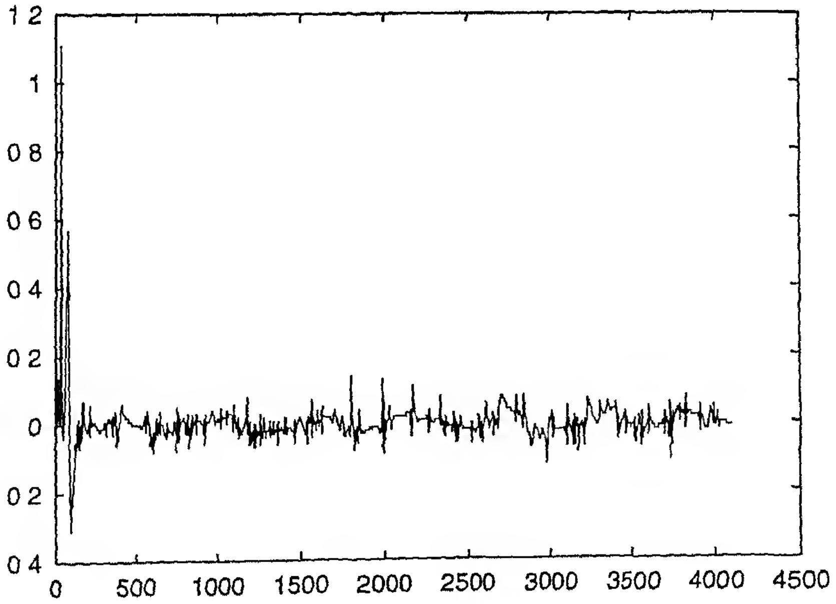

Figure 4 4 Reconstructed residual signal

of one beat of ECG signal after two band decomposition On the x axis the co ordinate of 200 roughly corresponds to 100 Hz

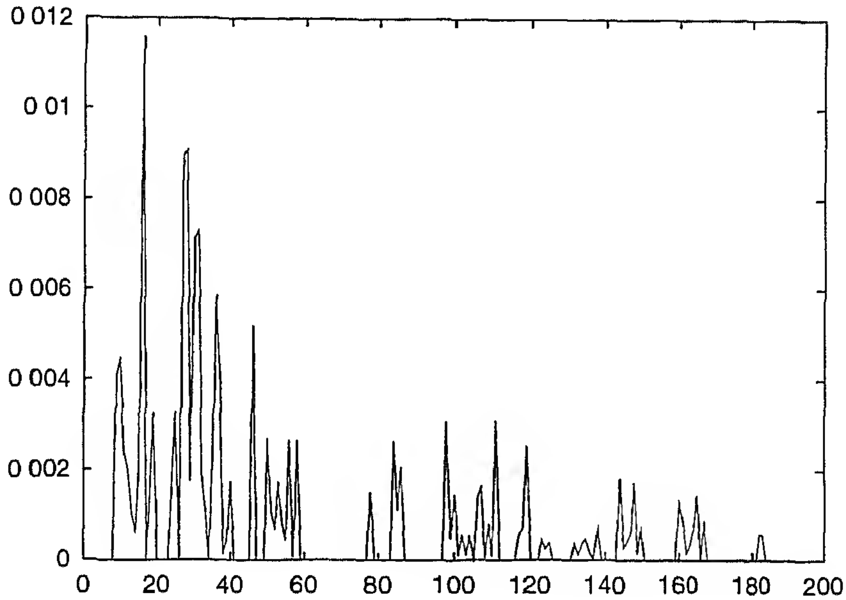

Figure 4 6 Absolute value of residual after 2 band decomposition

It is observed that there is considerable energy left in the region of 10–30 Hz This indicates that some predictable part still remains in the residual signal and it is not entirely white This is because the coefficients are unable to capture a sudden spike like the QRS complex Hence the use of AWP is justified and as will be seen it gives very good results

The next chapter describes the results effects of line interference and ability of the algorithm to retain the deformities

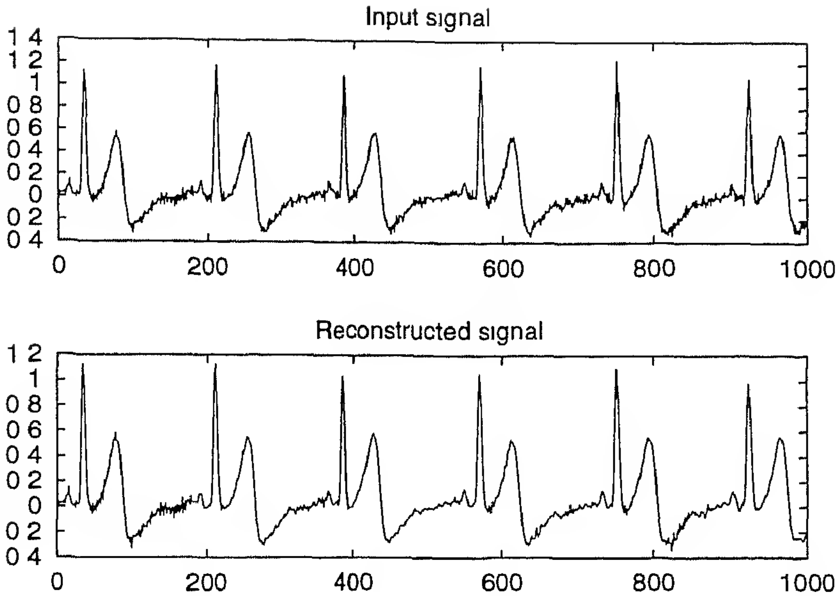

Figure 4 5 Input and reconstructed signal

percent root mean square difference (PRD) which is given by

$$\text{PRD} = \left[\frac{\sum_{i=1}^{N}(y(i) - y(i))^2}{\sum_{i=1}^{N} y^2(i)}\right]^{1/2} \times 100 \qquad (4\ 1)$$

where $y(i)$ is the original and $y(i)$ is the reconstructed signal It is to be noted that PRD as such is not a very good measure to judge the quality of the reconstructed signal In the ECG what is important is the diagnostability which can be judged only by a cardiologist The PRD is used here as a measure of distortion because it is most commonly used in literature

4 4 Justification for Decomposition of Residual

In any prediction scheme, whether it is the conventional short term prediction or the LTP, it is assumed that the frame under consideration is stationary The prediction coefficients capture the characteristics of the frame and the residual is essentially noise which has a uniform spectrum An AWP decomposition of the residual should not therefore give any compression Fig 4 6 shows the absolute value of the residual

of one beat of ECG signal after two band decomposition On the x axis the co ordinate of 200 roughly corresponds to 100 Hz

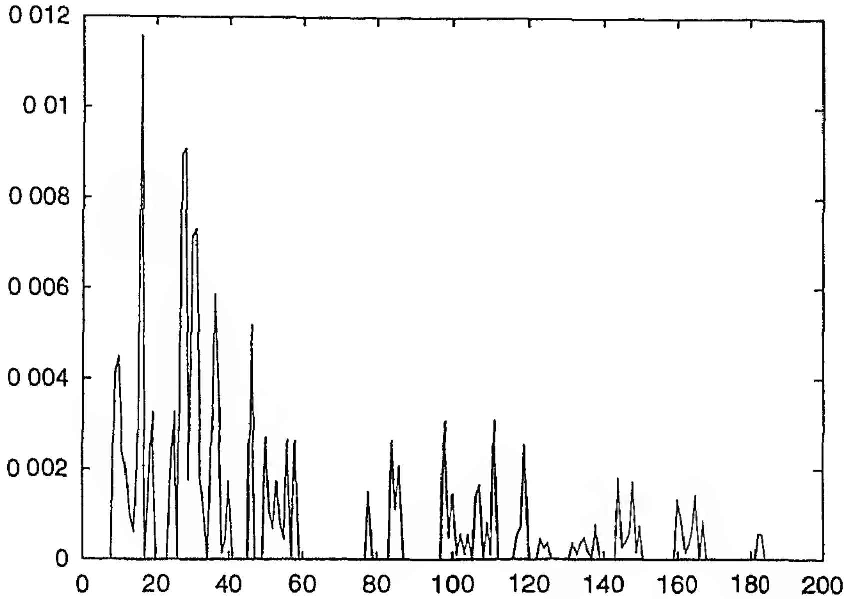

Figure 4 6 Absolute value of residual after 2 band decomposition

It is observed that there is considerable energy left in the region of 10–30 Hz This indicates that some predictable part still remains in the residual signal and it is not entirely white This is because the coefficients are unable to capture a sudden spike like the QRS complex Hence the use of AWP is justified and as will be seen it gives very good results

The next chapter describes the results effects of line interference and ability of the algorithm to retain the deformities

Chapter 5

Results

5 1 Effects of Lıne Interference

As mentıoned earlıer the algorıthm was tested on an ECG data pıcked up ın the laboratory The sıgnal ıs shown ın figure 5 1 Although a 50 Hz notch filter has been used the lıne ınterference has not been totally elımınated

There are basıcally two parameters whıch can be controlled to gıve dıfferent compressıon ratıos

1 Mınımum packet sıze If the mınımum packet sıze of decomposıtıon ıs ıncreased keepıng other parameters the same, the compressıon ratıo ıncreases Thıs ıs because as the packet sıze ıncreases percentage contrıbutıon of each coefficıent to the packet energy decreases and hence more coefficıents are dıscarded for the same threshold settıng

2 Energy threshold settıng As the energy threshold ıs decreased more coefficıents are dıscarded and hence hıgher compressıon ıs achıeved

As the compressıon ratıo ıncreases, the PRD of the reconstructed sıgnal also ıncreases Table 5 1 summaıızes the results obtaıned The correspondıng ınput sıgnal and the reconstructed sıgnals have been shown ın figures 5 1 – 5 7

The hıgh value of PRD ıs attrıbuted to the lıne ınterference Thıs can be justıfied as follows In the AWP decomposıtıon there ıs an ınherent filterıng effect and the

Energy threshold=0 1% of packet energy			
Packet size	Compression ratio	PRD	figure
64	8 97	14 81	5 2
128	9 12	15 56	5 3
256	10 99	17 5	5 4
512	13 75	20 38	5 5
1024	34 51	21 99	5 6
2048	43 45	23 89	5 7

Table 5 1 Results for data with 50 Hz noise

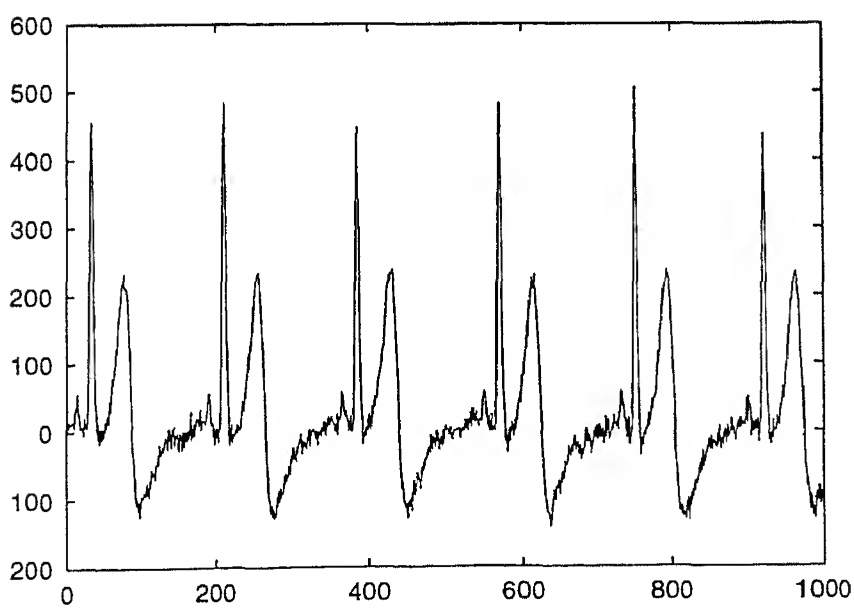

Figure 5 1 Input signal

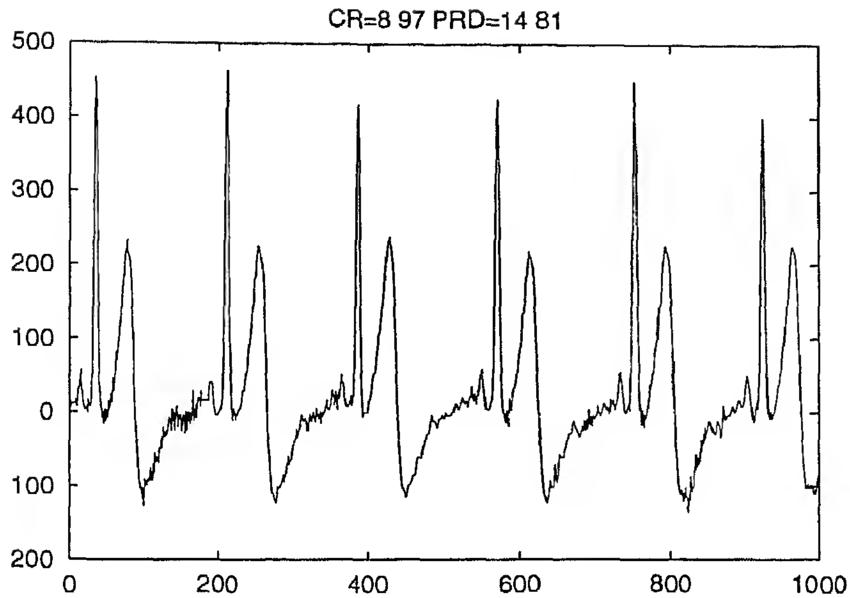

Figure 5 2 Reconstructed signal

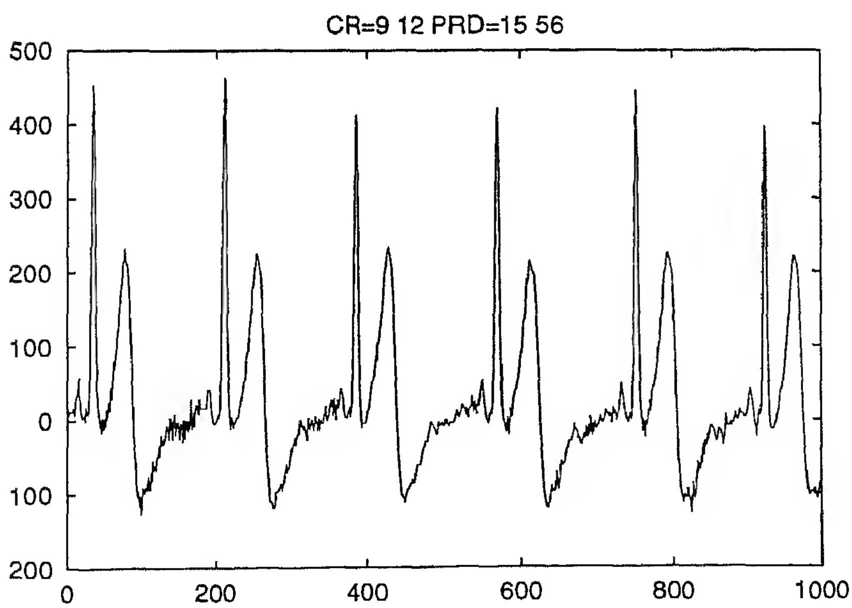

Figure 5 3 Reconstructed signal

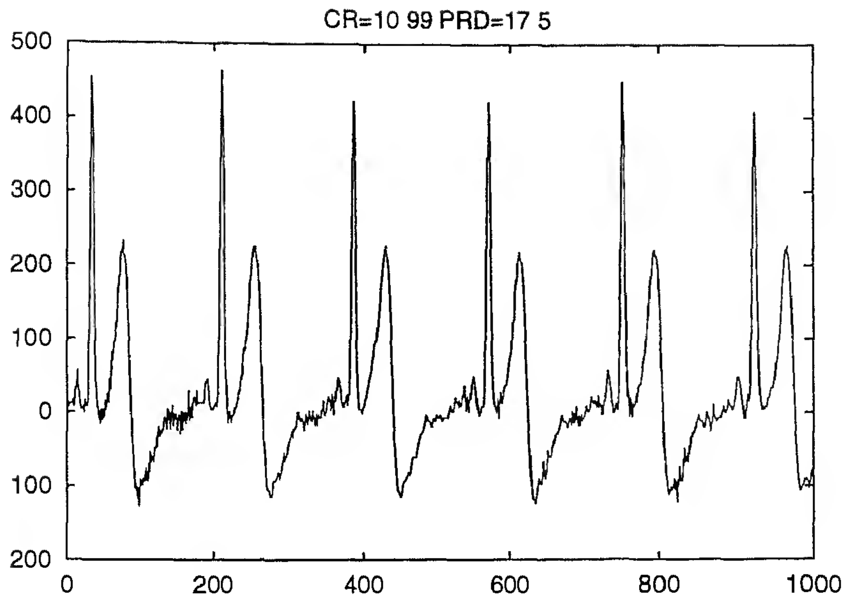

Figure 5 4 Reconstructed signal

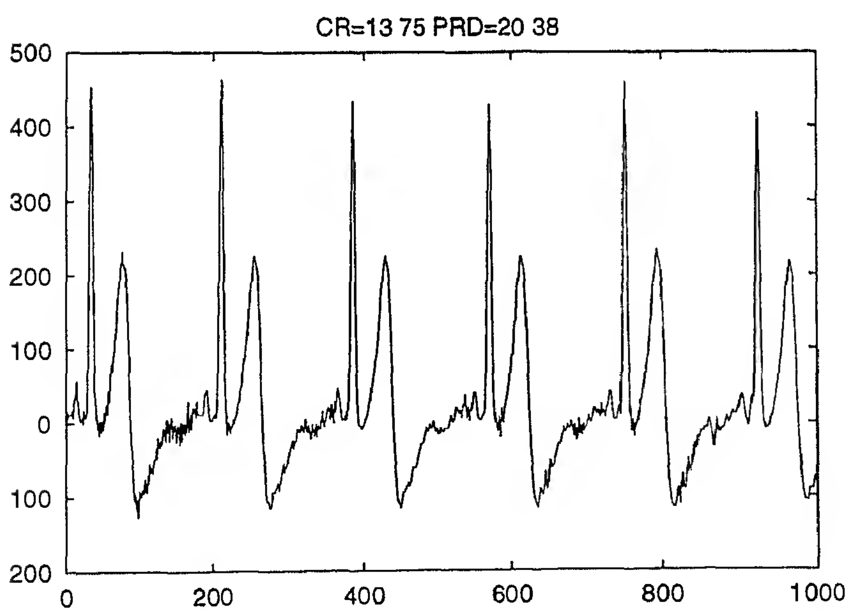

Figure 5 5 Reconstructed signal

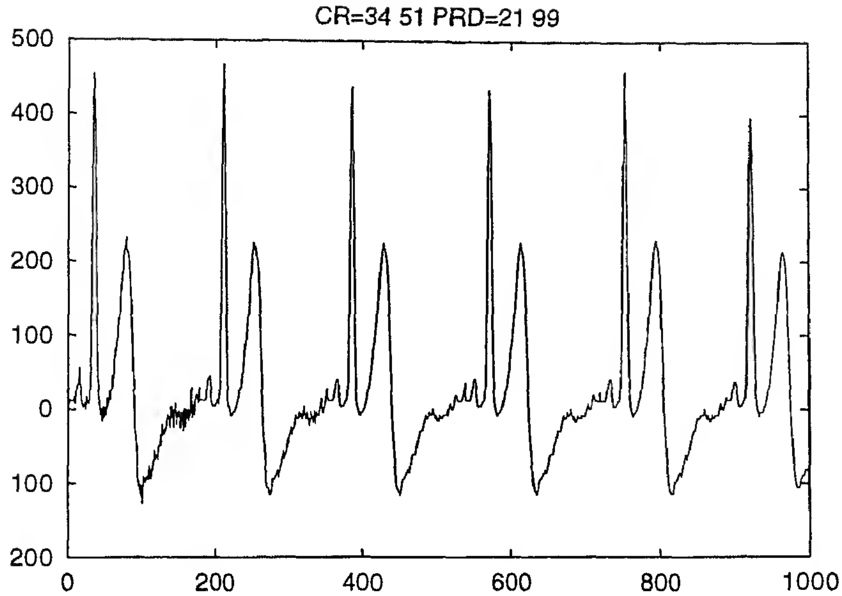

Figure 5 6 Reconstructed signal

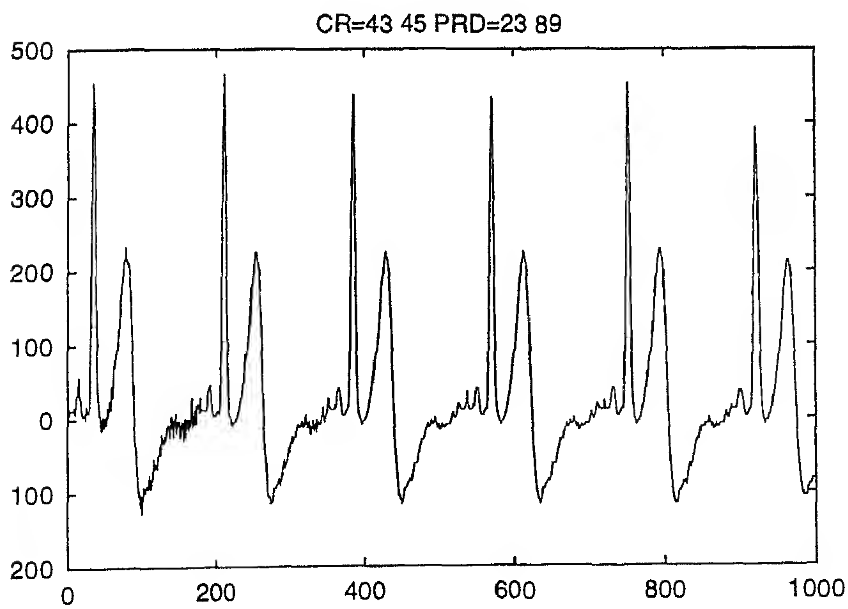

Figure 5 7 Reconstructed signal

reconstructed signal is considerably smoothed out as shown in figure 5 7 If this smoothed out signal is used as the input to the algorithm then much better results are obtained as given in table 5 2 The corresponding waveforms are shown in figures 5 8–5 14 It is observed that there is hardly any perceptible change for the reconstructed signal in figures 5 9–5 14 although there is a considerable change in PRD This clarifies the point mentioned earlier that the PRD is not a very good measure of quality and that the visual appearance of the reconstructed signal is more important for clinical purposes

Energy threshold=0 1% of packet energy			
Packet size	Compression ratio	PRD	figure
64	13 09	3 47	5 9
128	14 29	3 54	5 10
256	19 7	4 98	5 11
512	23 76	5 39	5 12
1024	30 72	6 93	5 13
2048	32 42	8 26	5 14

Table 5 2 Results for data without noise

The 50 Hz line interference also gives a much higher value of dynamic range for the residual in LTP method This is compared in figure 5 15 In the upper plot the dynamic range is high because the 50 Hz noise in the input is unpredictable whereas in the lower plot the dynamic range is low because the smoothed out signal has been used as the input Even if the AWP decomposition is used directly on the ECG signal as in [2] the results are much better for the smoothed out data The results are compared in table 5 3

5 2 Comparison with LTP and AWP

In [1] the authors have claimed a compressed bit rate ranging from 71 bits/second to 490 bits/second for an input bit rate of 2500 bits/second This corresponds to a compression ratio of 35 21 to 5 1 The PRD even for the lower bit rate is

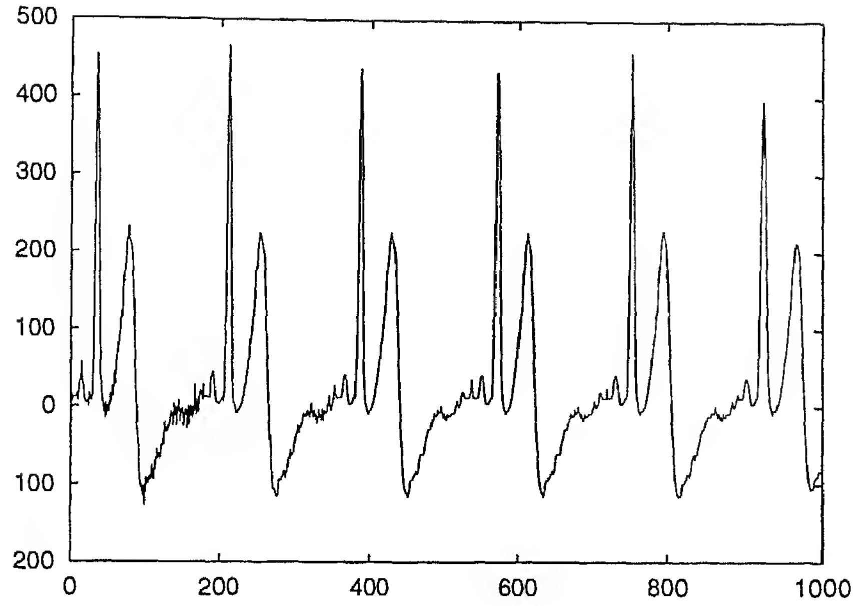

Figure 5 8 Input signal

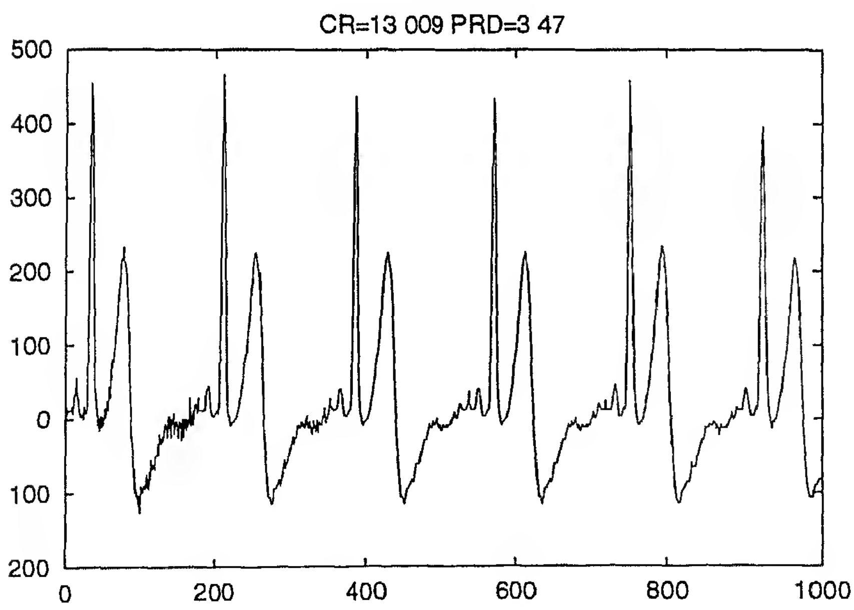

Figure 5 9 Reconstructed signal

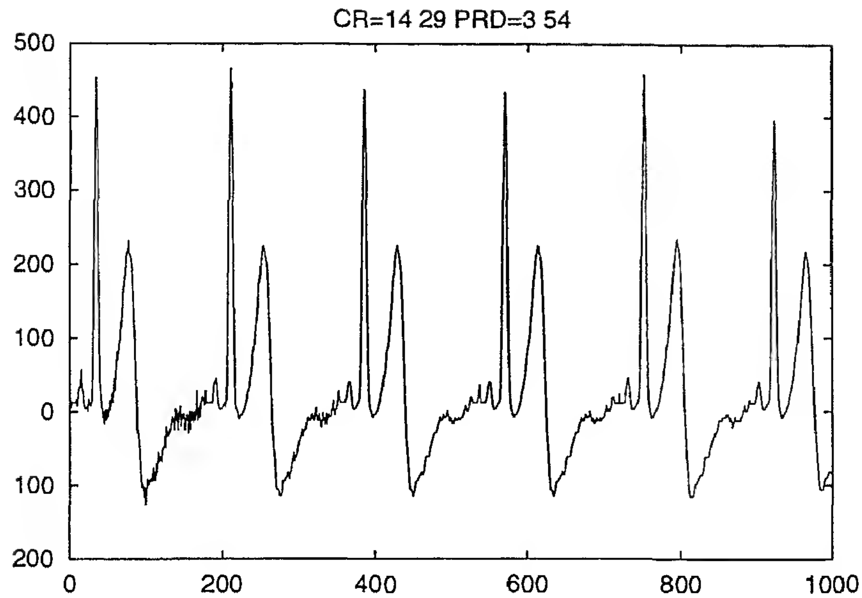

Figure 5 10 Reconstructed signal

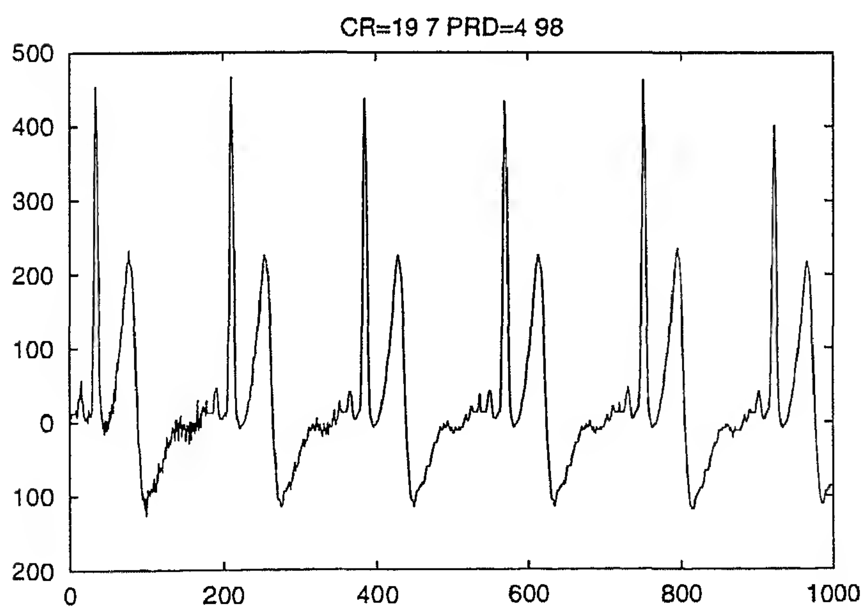

Figure 5 11 Reconstructed signal

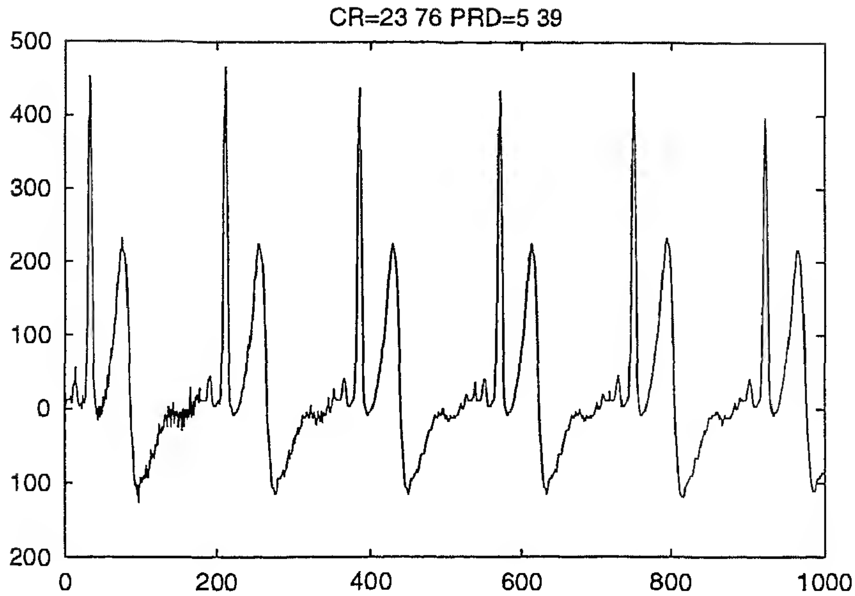

Figure 5 12 Reconstructed signal

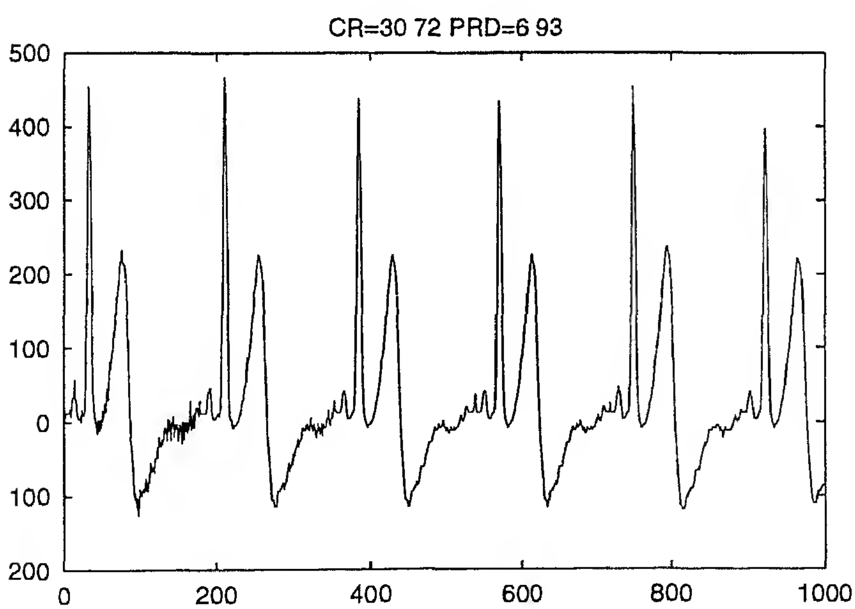

Figure 5 13 Reconstructed signal

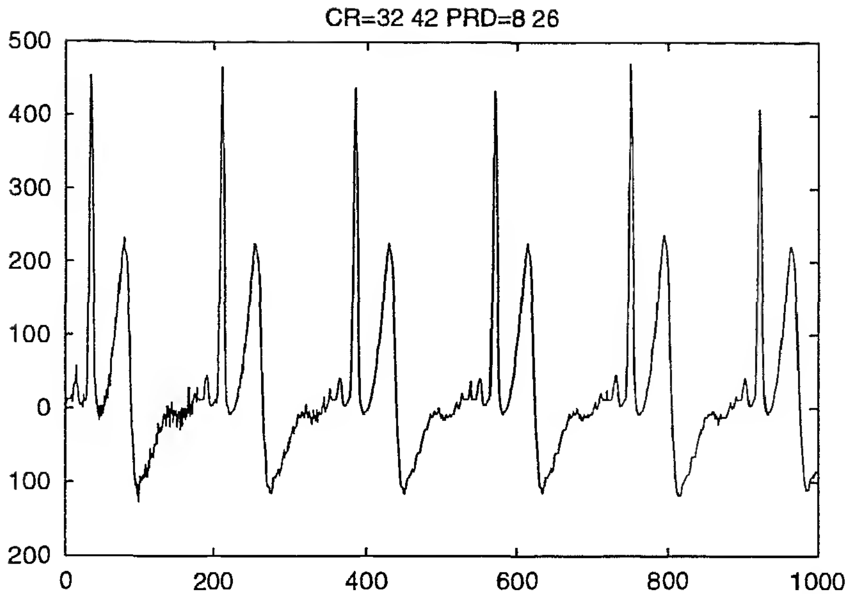

Figure 5 14 Reconstructed signal

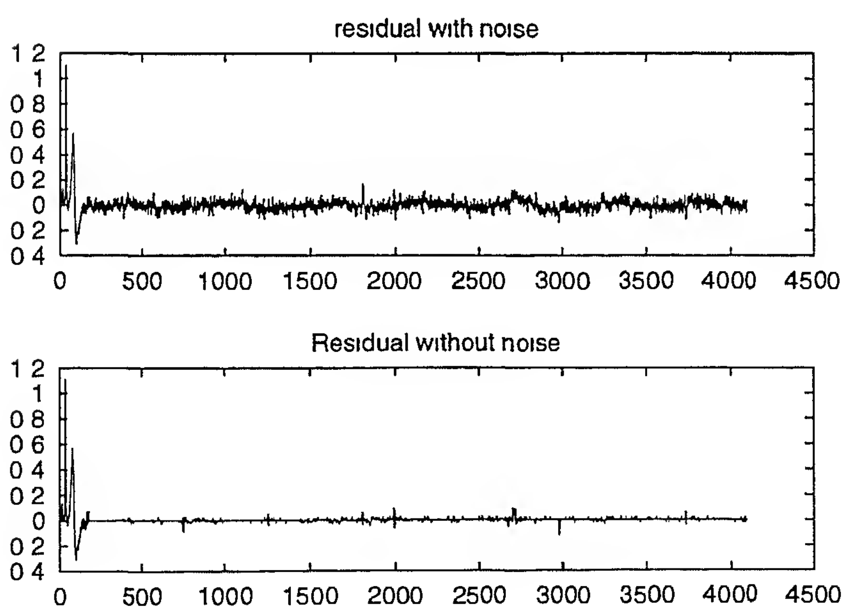

Figure 5 15 Residual signals with and without noise

LTP and AWP combined		Only AWP	
Compression Ratio	PRD	Compression Ratio	PRD
23 7	5 39	7 34	10 08
32 42	8 26	6 81	7 83

Table 5 3 Comparison with pure AWP method

below 10 percent but these results were tested on a database which is free of any line interference In practice it is very difficult to eliminate this line interference especially for ambulatory ECG recordings In such cases LTP method would not give good results The dynamic range would also shoot up in case of any abnormality in isolated beats In [2] the authors have claimed a compression ratio of 10 62 for a PRD of 5 92 percent The results obtained by combining LTP and AWP on the smoothed out data as indicated in table 5 2 is much better

5 3 Retention of Abnormalities

Certain kinds of diseases require long period of monitoring because the abnormality may appear just in a few beats in several hours of recording The compression decompression scheme should be able to retain these abnormalites even in isolated beats because they have a great amount of diagnostic significance The algorithm was tested for various abnormalities [11] which were artificially simulated The various thresholding parameters were held constant and the abnormalities were tested The results are shown in figures 5 16–5 23 In all the figures the upper trace is the input and the lower trace is the reconstructed signal It is seen that the algorithm is self adaptive For slowly varying abnormalities (figures 5 18,5 19) the high compression ratio and low PRD is maintained For sharply varying deformities either the compression ratio (figures 5 20,5 21) or the PRD (figures 5 16 5 22 5 23) is affected In some cases (figures 5 16 5 22) noise is added in the beat after the deformed beat in the reconstruction The results are summarized in table 5 4

Deformity	Indication	CR	PRD
Increase in QRS width	Intraventricular conduction defect	17 22	11 02
Decrease in QRS amplitude	Myxoedema and pericardial effusion	14 87	6 04
Absence of P wave	Auricular muscle disease	14 94	4 41
Increase in T wave amplitude	Thyrotoxicosis	19 7	8 79
Diphasic T wave	Digitalis	13 58	5 2
Notching of T wave	Paroxysmal tachycardia	12 72	3 93
T wave inversion	Myxoedema	19 12	16 64
Beaked T wave	Pericarditis	21 54	10 57

Table 5 4 Results of algorithm on common abnormalities

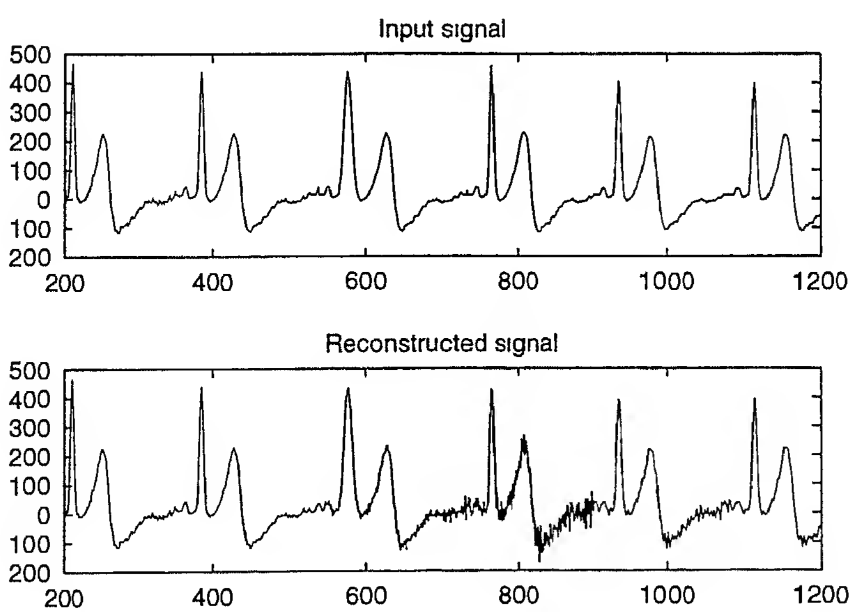

Figure 5 16 Increase in QRS width

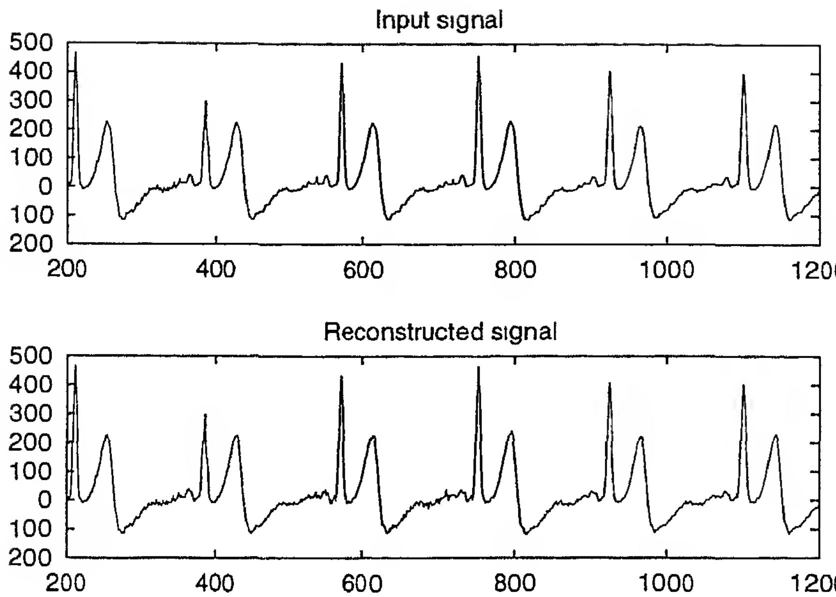

Figure 5 17 Decrease in QRS amplitude

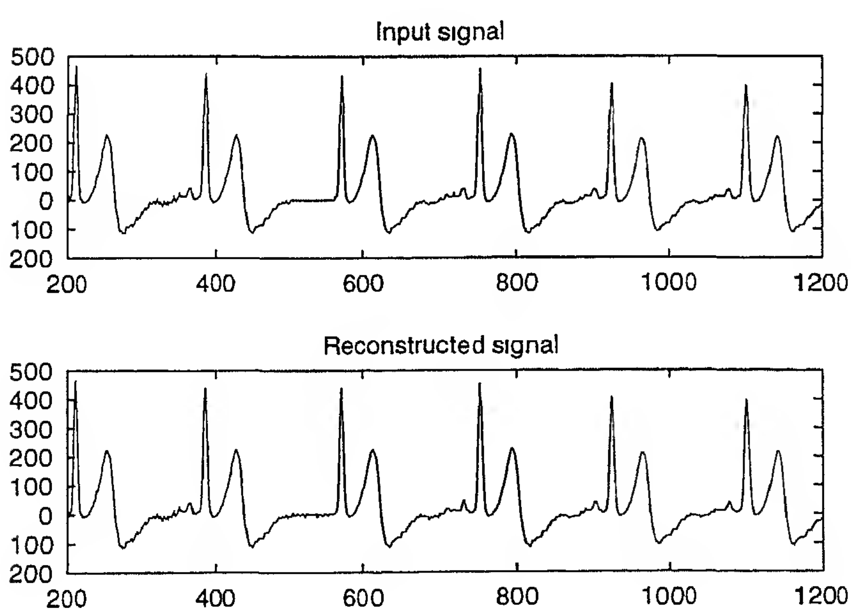

Figure 5 18 Absence of P wave

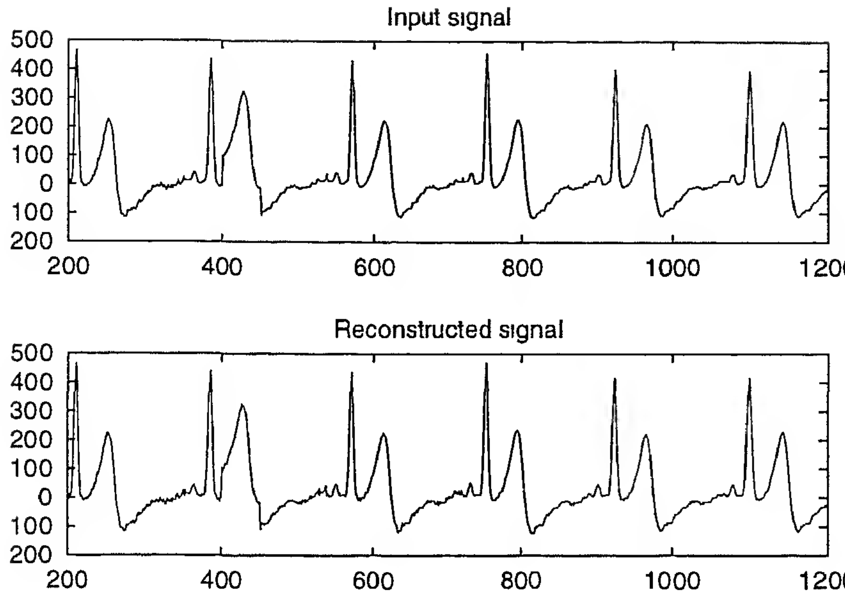

Figure 5 19 Increase in T wave amplitude

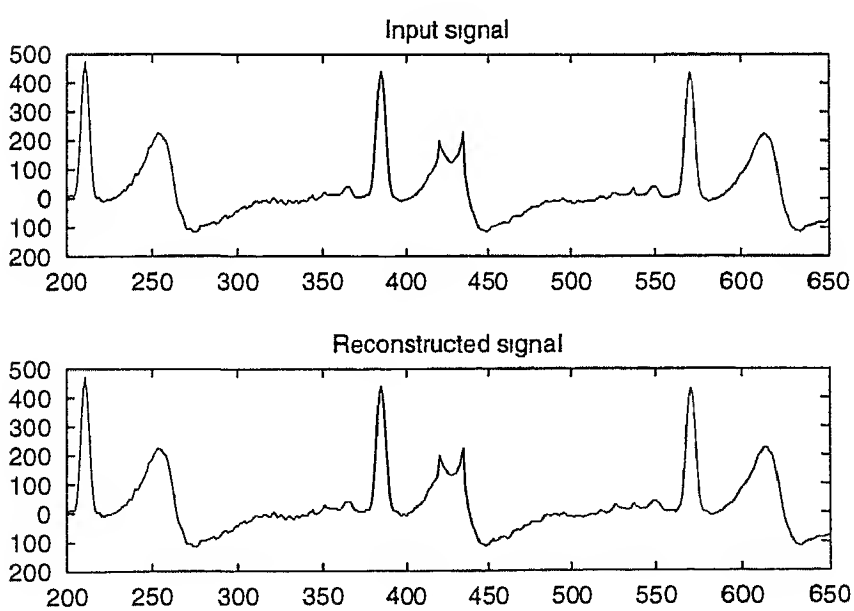

Figure 5 20 Diphasic T wave

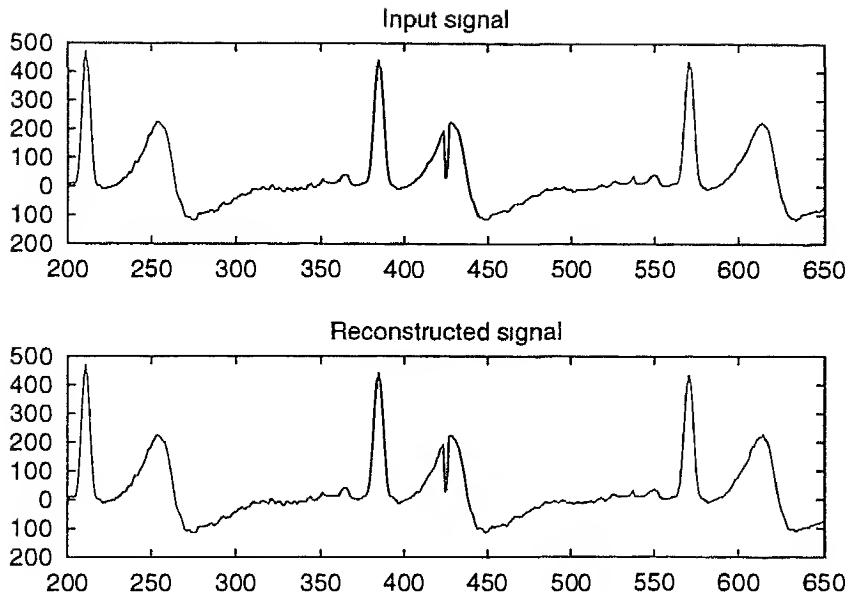

Figure 5 21 Notching of T wave

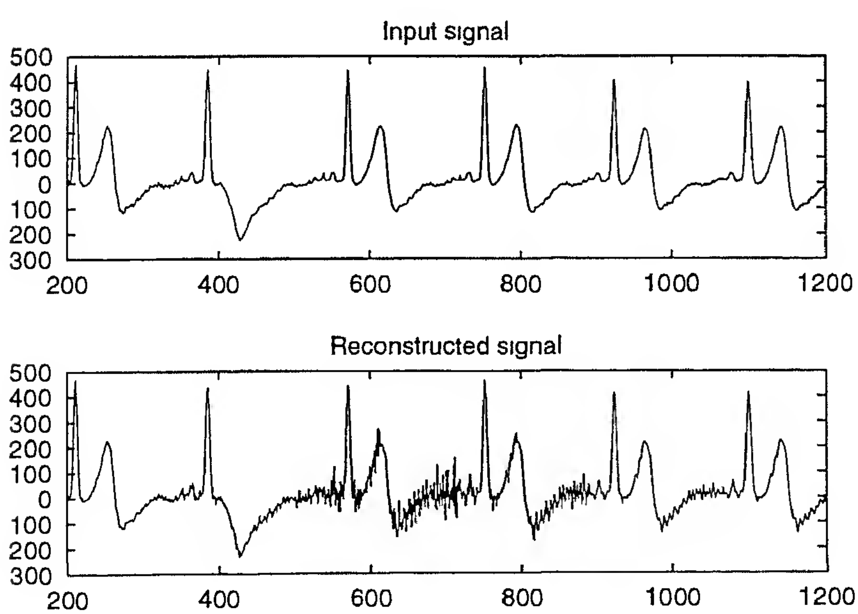

Figure 5 22 T wave inversion

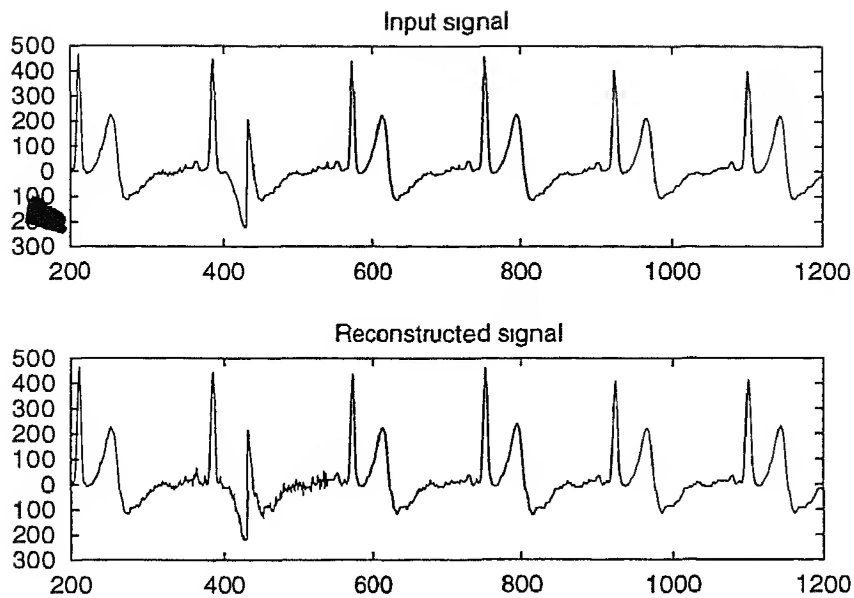

Figure 5 23 Beaked T wave

5 4 Future Work

One of the major problems faced during the thesis work was lack of a good data base Most of the algorithms presented in literature have been tested on very good data bases like the MIT data base which is free of any line interference Secondly the abnormalities were tested on simulated data First of all, the algorithm should be tested on a standard data base like the MIT data base This will help in the direct comparison of its performance with other algorithms This algorithm was tested by writing a C program on HP work stations The CPU time for compression-decompression of 20 seconds of data is in the order of mili seconds and so real-time operation is not a problem The algorithm can therefore be implemented on an ADSP chip and can lead to the development of an indigenous Holter ECG equipment

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